Renewable and Sustainable Energy Reviews 22 (2013) 506–514

Contents lists available at SciVerse ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Bidding of price taker power generators in the deregulated Turkish power market

Ahmet Yucekaya *

Department of Industrial Engineering, Kadir Has University, Fatih, Istanbul, Turkey

ARTICLE INFO

Article history:
Received 6 September 2012
Received in revised form
14 January 2013
Accepted 20 January 2013
Available online 15 March 2013

Keywords:
Price-taker bidding
Bidding into market
Monte Carlo simulation
Deregulation

ABSTRACT

In deregulated power markets, power firms bid into the day-ahead power market either with buy offers or sell offers. The auction mechanism and competition determine the equilibrium price and quantity for each hour. If the bid price of a company is below the market clearing price, then the offer of the company is accepted and rewarded with the market price. A company can be a price maker or price taker depending on the capacity it offers to the market. A price-taker unit must determine the right offer that will maximize their profit given price uncertainty and blind auction rules. This paper first examines power supply in the Turkish electricity market and bidding process. Then a marginal cost-based Monte Carlo method is developed to determine hourly and block bidding strategies of price taker units. Historical market prices are then implemented in a normal distribution to generate hourly price scenarios. A solution methodology is developed that maximizes the expected profit of each hourly and block bidding strategy over price scenarios. The generator is able to both evaluate the hourly bidding and block bidding strategies and find the best bidding strategy that will be submitted to the market using the proposed methodology. The model is illustrated for two coal units in Turkish power market and the results are presented.

© 2013 Elsevier Ltd. All rights reserved.

Contents

1. Introduction

One of the main market competition structures used in newly deregulated markets is the poolco [1]. A poolco market is a central auction that brings regional buyers and sellers together. All competitive power generators (supply) and buyers (demand) are required to submit blocks of energy quantities and corresponding prices they are willing to receive from or pay into the pool. The prices and quantities submitted by the market participants are binding obligations as they require financial commitments to the market. Once all the supply and demand bids have been submitted and the bidding period ends, an Independent System Operator (ISO) ranks these quantity-price offers based on the least-cost for selling bids and the highest price for buying bids. The ISO then matches the selling bids with buying offers such that the highest offers are matched with the lowest selling bids. The market clearing price (MCP) occurs at the point where the demand is met. All sellers whose bids are below the MCP are paid MCP which is called uniform pricing. It is also possible for a company to get its offer price paid. This strategy is rare and called pay-as-bid strategy. The former strategy is preferred by market authorities to lower market prices.

The electricity supply industry has unique features such as a limited number of producers, large investment size (which makes it more difficult to enter the market), transmission constraints (which are obstacles for consumers to effectively reach many generators), and transmission losses (which discourage

* Tel.: +90 212 5335765.
E-mail address: ahmety@khas.edu.tr

1364-0321/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.rser.2013.01.038

consumers from purchasing power from distant suppliers) [2]. These features force market players to be more aggressive with their bidding strategies, and it also makes them construct models that carefully take into account their constraints and the uncertainty of the market price.

The deregulated electricity market usually has a few generators (market suppliers) that tend to dominate the market, making the market seem more similar to an oligopoly. In such oligopolistic markets, an individual generator can exercise market power and manipulate the market price via its strategic bidding behavior [3]. On the other hand, a price taker unit does not have the power to change the market price and must be willing to accept the market price. Companies have to determine bidding strategies so that they can make a profit even if they are price takers and do not dominate the market. There are several approaches to analyzing and developing bidding models. The bidding strategies used in the market are discussed in [4] which include a literature survey of the current approaches to the bidding problem. The game theory approach is commonly used in the literature to model the behavior of market players [5]. The idea is to model the interactions given that the reaction of a market player is affected by other players' actions. Several methods used in modeling bidding strategies are explained in [6]. The authors compare the game theory approach with the conjectural variation-based method. In both approaches, each firm in the market rationally tries to maximize its profit while considering the reactions of its competitors. They show that firms can increase their profit by using the conjectural variation-based method, and the equilibrium found corresponds to the Nash equilibrium.

In [7], a genetic algorithm is used to solve the bidding problem. Although the solution obtained is a heuristic one, it could be used by a company in its daily bidding process. The authors explain the process of bidding and how the equilibrium price is determined. They construct their model based on the assumption of exogenous prices. In [8], an optimization tool to determine a bidding curve for the Ontario power market was developed. The authors used different scenarios of market prices and load. The decision process for the generator is based on the probability distribution of forecasted prices. The model assumes exogenous prices and includes operational constraints such as ramp-up limits, start-up limits and minimum up-down times. In [9], bids are represented as quadratic functions of power levels. The model optimizes the parameters of each function during a two-phase process. In the first phase, the ISO minimizes the total system cost in which the parameters for other generators are known. In the second phase, solutions are plugged into the generator's model. The Lagrangian relaxation procedure is used to solve the expected cost minimization problem.

In [2], the authors assume that suppliers bid linear supply functions; the coefficients of the functions are chosen for each supplier in such a way that the expected profit is maximized subject to the behavior of one's rivals. They formulate a stochastic optimization model and use a Monte Carlo-based method to tune the parameters of the function. They also include the level of information known for each generator in a symmetric and asymmetric market. In [10], the authors develop a lognormal distribution-based price generation method and solve an MILP to find the bidding strategy for a price taker generator. They use historical prices to approximate a lognormal distribution and estimate a confidence interval for the hourly prices. Then a convex bidding curve is estimated that maximizes the profit for power price scenarios. In [11], a stochastic programming model is introduced for a price taker hydro electricity unit. They employ historical data to validate the model. A stochastic linear programming model and a case study for a price taker Norwegian company is developed in [12].

In [13], the authors propose a profit maximization model for price taker units in a day-ahead market in which risk is involved. They include energy sales with bilateral contracts, a spot market and options in the market, and the main objective is to determine the best course of trading action when there are normally distributed power prices. A bilevel programming and particle swarm optimization (PSO)-based method is developed for strategic bidding in competitive electricity markets in [14]. They assume that the competitive power market is based on a multileader-one-follower nonlinear bilevel model in which each player tries to maximize profits through strategic bidding. On the other hand, the system operator tries to minimize the overall cost by solving the PSO-based problem while dispatching the lower cost generators. In [15] a probabilistic model for a price taker Genco is developed in which a marginal cost-based bid determination method is employed. The authors estimate the market prices using a statistical distribution and then based on the power quantity and corresponding bid price of marginal cost they determine the profit of the Genco. In [16], the authors develop a stochastic optimization model for a generator which submits a bid as a premium and strike price in energy call option auctions. The uncertainties in fuel supply and fuel switch options are included, which makes the problem more complex. The objective of the model is to find the bidding strategy that ensures a desired rate of return taking into account uncertain fuel supply and risk constraints. In [17], the authors review the models for optimization-based bidding in day-ahead markets. The models are classified as price takers and nonprice takers and then classified as linear and nonlinear integer mathematical programs with equilibrium constraints and stochatic models. In [18], a bielevel programming algorithm is developed to determine the strategic bidding for a Genco in a transmission constrained environment. The first level maximizes the profit of the Genco and the second level minimizes the cost of the independent system operator to minimize consumer payoff. The authors present a method to identify a bidding strategy for pumped hydro storage systems in a pool-based electricity market in [19]. The operation of a pumped storage system requires significant effort and it needs to be combined with the bidding strategy as the market price also affects the cost of power consumption. In [20], the authors present their research on optimal bidding strategies for Gencos in an environment where bilateral contracts and transmission constraints exist. The problem is modeled as a bi-level optimization algorithm in which in the first step each player maximizes its own revenue without considering transmission constraints and in the second stage the transmission constraints are included and units are dispatched.

Much research in the literature has been conducted on market price forecasting. Stochastic time series methods, casual models, statistical distribution based methods, artificial intelligence models [21], neural networks [22,23] and the Wavelet neural network based method [24] are some examples of this research.

The bidding mechanism is actively used in most deregulated power markets in developed countries. The auction mechanism has been successfully implemented in power markets such as in the USA, Canada, West Europe, Japan, and Hong Kong. The uniform pricing scheme is the preferred pricing method. However, the time period for which the bid is valid varies. The liberalization of the electricity industry is relatively new in the Middle East, Balkans, Russia and Caucasus. The developing economies and the largest countries in region, which are Russia, Turkey and Iran, began privatization roughly in the same time period. Russia started to liberalize electricity prices in 2007 and the plan was to fully liberalize the market by 2011 [31]. Iran is also in the process of liberalizing the electricity industry, and has begun to transfer state-owned plants to private owners. The market

structure is different in each of these countries, and all of themhave attained some level of deregulation [32]. Due to the fact that Iraq and Syria have been plagued by war and a unstable political environment for the past few years, the electricity industry is still state-owned and controlled but they have welcomed private investors for power plant investments. Greece and Bulgaria, which are members of European union, have undergone privatization and deregulation of electricity as in many European states, and they have benefited from this experience. In the many smaller countries in the region, such as Georgia, Armenia, Macedonia, Albania and Bosnia [33], the political and economical conditions are not yet conducive for privatization and deregulation of the markets.

The Turkish power market began to be deregulated in 2001, and daily bidding was implemented in 2011. Each day ISO announces the hourly power demand for the next day until 11:30. After the bilateral transactions between power sellers and consumers are deducted, the remaining amount of power is provided from the market. Each power producer submits an offer to get a chunk from this demand. The offer consists of a price ($/MW h) and corresponding power quantity (MW h) [25]. A company can submit an offer for each hour of the next day which is called hourly bidding. Alternatively, a company can submit an offer for the whole day and this offer would be accepted whenever the bid price is less than the power price. In this paper, two different models are developed for different bidding alternatives and a solution methodology is proposed for a price taker company. Section 2 gives the details of the bidding process and development stages in Turkish power market. Section 3 provides the model development and notation. The solution approach is given in Section 4. The case study is given in Section 5 and conclusions are provided in Section 6.

2. Bidding process in the Turkish power market

State directed regulations for the restructuring of electricity markets started in 2001 with the founding of the Energy Market Regulatory Authority (EMRA). Law 4628 aims for the deregulation of the electricity industry and the privatization of assets that used to belong to the state. According to this law, the electricity industry is to be divided into smaller and managable pieces in which generation, transmission and distribution are handled by different companies. The EMRA is the main authority that manages this process and oversees all related activities. The monopoly of state-owned resources is divided up into different companies such as EUAS (generation), TETAS (trading), TEDAS (distribution) and TEIAS (transmission). The main objective is to increase efficiency and provide a competitive market environment which can lower the cost of electricity and increase the reliability of power supply. The first step of the market design, which involves financial transactions in a deregulated electricity market, started on December 1, 2003. The power supplier and large number of consumers were encouraged to participiate and invest in power markets at this time. The second step of the market design was defined as balance and conciliation, and it was launched on August 1, 2006. Participants carried out bidding and bilateral contracts in this step until the end of 2009. After this, participants started to submit monthly capacity and bids along with their schedules and a final market environment became active at the end of 2011. Currently, a day-ahead planning and a day-ahead market structure are employed in which the auction mechanism determines the MCP.

On a typical day, the estimated day-ahead demand for each hour of the next day is announced by the ISO. The offers from the demand side (buyers) are also considered during this process. Each participant submits the amount of power they will supply, using bilateral contracts. These contracts are agreements between two parties that allow each participant to determine the power delivery conditions and price. The total amount of power that will be provided with the bilateral contracts is determined and deducted from the total estimated demand. Fig. 1 shows the estimated demand and amount of power that was provided with bilateral contracts on July 17, 2012. The remaining amount should be supplied from competitive and reliable offers in the market. Hence, this is suportive of open competition [25].

The day-ahead process is divided into two different entities: the day-ahead planning and the day-ahead market. It is obligatory to submit the available capacity to the day-ahead planning so that the ISO can observe the status of resources. On the other hand, it is not obligatory to join to the day-ahead market and submit an offer.

The market participants include the wholesale supplier, power plants, independent generation units and state resources that have the available capacity to submit sell bids to obtain power from day-ahead demand. In day-ahead planning, the main objective is to balance the supply and demand. On the other hand, in a day-ahead market, the objective of each participant is to maximize its portfolio. The planning allows the system operator to balance generation with buy requests submitted by market participants without considering the offer prices. In a day-ahead market, suppliers and buyers can balance their portfolio based on price levels. It is possible to submit hourly and block offers each day in both. Table 1 shows the order of activities in a day-ahead market on a typical day [25].

The bilateral contracts should be submitted before the day-ahead planning begins. The contracts are submitted until 16:00 on the day before the day-ahead. Each participant is required to submit the available capacity and status of their resources by 9:30. The ISO estimates the day-ahead demand for each hour of

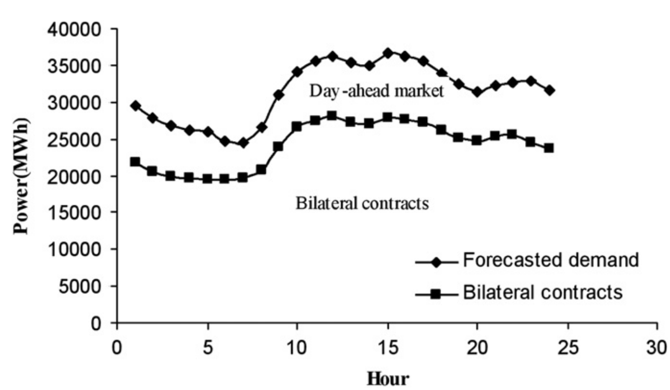

Fig. 1. Estimated power demand and bilateral contracts, July 13, 2012.

Table 1
Activities in a day-ahead market.

Daily activities	Time
Submit the bilateral contracts (before day-ahead)	16:00
Submit the available capacity	09:30
ISO determines the day-ahead demand and constraints	11:30
Submit buy/sell bids	11:30
Verify the bids	12:00
ISO determines the hourly day-ahead market prices and dispatched resources	13:00
Submit the objections	13:30
ISO announces the final results	14:00
The operational day begins	00:00

the next day based on the temperature, submitted buy offers, bilateral contracts, and historical data. It is expected that there will be deviations from the estimated demand, as the demand and power consumption have stocthastic and unpredictable features. The ISO also considers the transmission and outage constraints that affects dispatch decisions. Once the amount of power provided from the bilateral contracts is deducted, that amount of power must be supplied from the market for each hour. Each market participant submits buy and sell bids to the market at 11:30 and verifies the bids by 12:00 noon. The bids can be block bids or hourly bids that consist of power price and correspoding power quantity. ISO runs a security constrained cost minimization program to optimize the schedule of the resources. It is essential to order the sell offers from cheapest to highest and order the buy offers from highest to cheapest. Then the market clearing price for each hour is determined based on the offers and constraints, and then announced by the operator. Each market participant is allowed to submit an objection within a given time limit. The final results are released after objections are resolved or the program is updated based on the requests. The program starts operation at midnight and runs for 24 h. It is worth noting that usually 10–15% of power is supplied from the day-ahead market. Fig. 2 shows the structure of the Turkish electricity market.

Almost 80–85% of demand is still supplied using bilateral contracts. The idea of dergulation and its mechanism are not widely known or understood, as it is still under development and is relatively new. Power companies and large consumers still prefer to have bilateral contracts as the risk is low and it does not require dealing with a market mechanism. The contracts are usualy prepared months or years ago before day-ahead activities. In this system, the day-ahead market and real-time balance should be considered together. The schedule for the day-ahead market is determined 10 h before the actual day. On the other hand, the real time balance or real-time market is used to balance deviations from the estimated demand or planned schedule. Zero to five percent of electricity is handled in real time balance in which hourly decisions are effective. Generators, wholesale suppliers and consumers are allowed to submit bids to the day-ahead market or real-time balance. A supplier can submit in a day-ahead market or have reserves to be used in a real time balance. This reserve should also be offered to the real time market and hence the power that is not supplied through bilateral contracts and day-ahead market can be supplied in real time balance. The system operator determines the real time market price that will be used to calculate the payments for each resource in the real-time market. The system operator calculates the revenue or cost of each market participant based on the day-ahead market price, real time price and amount of power supplied from each resource. This process is called financial concilliation, in which each party is billed for the consumption or rewarded for the supply of power. The derivative market in Turkey began operations in 2005, and the operations for electricity options started in November 2011, and as such is relatively new. Financial products such as futures, forwards and options are generated and financial transactions are completed in a financial concilliation stage. This is usually weeks or months after the operation day.

The demand for energy in Turkey is increasing to an extent almost parallel to the economic growth of the country. The country has an average economic growth of 7%, and this entails increasing industrial production, new investments, and a growing population, all of which drive up the demand for energy. The available generation capacity is dominated by coal-based resources and natural gas-fired plants. A nuclear power plant project has been proposed but it is still in the development stage, and is expected to be operational in 2015. As a result, the available capacity should be used efficiently through the proper planning and scheduling of power resources. The objective of deregulation in Turkish market is to successfully reach this point by providing a competitive market environment.

3. Model development for a price taker unit

The cost of the energy produced by the generating unit is dependent on the amount of fuel consumed, and it is typically approximated by a quadratic cost function $C(q)=a_1+a_2q+a_3q^2$ (\$/MW), where q is the amount of energy generated in 1 h [26–28]. The coefficient a_1 represents the fixed cost or no-load

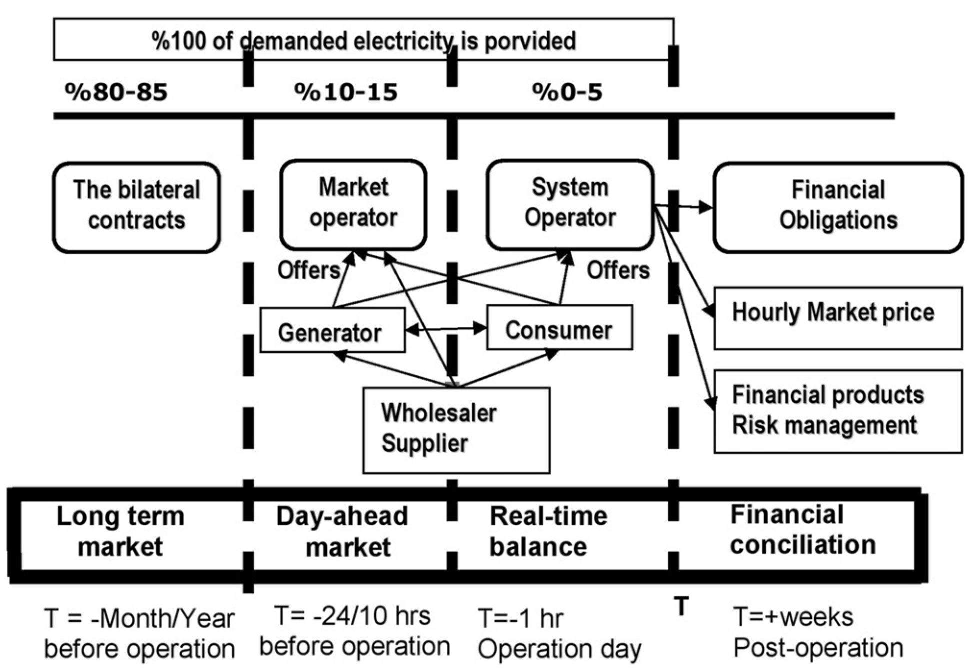

Fig. 2. Turkish power market after deregulation.

cost for each hour. This cost includes the labor and the cost of non-direct goods necessary to produce power for the corresponding hour. The value a_2 represents the linear cost which is proportional to the amount of power produced. The parameter a_3 is the quadratic cost coefficient and it is related with the amount of fuel used to produce electricity [27].

Generators use a single cost function when they bid into the market but it is also possible to combine the number of cost functions and get an approximated cost function. Most of the time, this approach is used by firms which have several generators and prefer to bid into the market using portfolio-based cost functions. Generators also have start-up costs, minimum-load operating costs and minimum up-down constraints. These are also used by the ISO when bids are evaluated [29].

In the block bidding method, a company submits an offer that consists of a power quantity and corresponding price to be accepted by the market whenever the market price is higher than the offer price. The mathematical model of the block bidding problem is presented below [30]:

$$P(\boldsymbol{q}_b,\boldsymbol{b}_b) = \underset{\boldsymbol{q}_b,\boldsymbol{b}_b}{Max}\, E[\text{Profit}] = \frac{1}{K}\sum_{k=1}^{K}\sum_{t=1}^{T}[P_t^k q_b^k - C(q_b^k)]$$
$$\text{for}\quad k=1,\ldots,K;\quad t=1,\ldots,T \tag{1}$$

Subject to the following constraints:

$$0 \le b_b^k \le B^{\max}\quad \text{for}\quad i=1,\ldots,N. \tag{2}$$

$$0 \le q_b^k \le Q^{\max}\quad \text{for}\quad i=1,\ldots,N. \tag{3}$$

$$q_t^k = \begin{cases} q_b^k & \text{if}\quad b_b^k \le P_t^k \\ 0 & \text{otherwise} \end{cases}\quad \text{for}\quad k=1,\ldots,K;\quad t=1,\ldots,T \tag{4}$$

$$C(q_b^k) = a_1 + a_2 q_b^k + a_3 (q_b^k)^2\quad \text{for}\quad k=1,\ldots,K \tag{5}$$

In the hourly bidding method, a company submits an offer consisting of a 24-h power quantity and corresponding price blocks for each hour to be accepted by the market whenever the market price is higher than the offer price for that hour. In other words, the player bids for each hour. The mathematical model of the hourly bidding problem is presented below.

$$P(q_t,b_t) = \underset{q_t,b_t}{Max}\, E[\text{Profit}] = \frac{1}{K}\sum_{k=1}^{K}\sum_{t=1}^{T}[P_t^k q_t^k - C(q_t^k)]$$
$$\text{for}\quad k=1,\ldots,K;\quad t=1,\ldots,T \tag{6}$$

Subject to the following constraints:

$$0 \le b_t^k \le B^{\max}\quad \text{for}\quad i=1,\ldots,N. \tag{7}$$

$$0 \le q_t^k \le Q^{\max}\quad \text{for}\quad i=1,\ldots,N \tag{8}$$

$$q_t^k = \begin{cases} q_t^k & \text{if}\quad b_t^k \le P_t^k \\ 0 & \text{otherwise} \end{cases}\quad \text{for}\quad k=1,\ldots,K;\quad t=1,\ldots,T \tag{9}$$

$$C(q_t^k) = a_1 + a_2 q_t^k + a_3 (q_t^k)^2\quad \text{for}\quad k=1,\ldots,K; \tag{10}$$

The notation of the parameters and decision variables for both methods are collected and presented below:

Parameters

$C(q)$	Cost of generating q MW ($)
a_1,a_2,a_3	No-load, linear, and quadratic coefficients of the generator's cost function
P_t^k	Market clearing price at hour t of scenario k ($/MW h)
$Q^{\max}$	Maximum generation capacity of the unit (MW h)
$B_{\max}$	Maximum allowable bid price in the market ($/MW h)
σ_t	Standard deviation of the market price at time t

Decision variables

b_b^k	Bid price of block bidding of scenario k ($/MW h)
q_b^k	Bid energy amount of block bidding of k (MW h)
q_t^k	Total energy generated at hour t of scenario k (MW h)
b_t^k	Bid price of hourly bidding at hour t of scenario k ($/MW h)
q_t,b_t	Bid energy amount and price of hourly bidding at hour t
q_b,b_b	Bid energy amount and price of block bidding

4. Solution approach

A price taker market player should first figure out a way to maximize its expected profit over a set of uncertain market prices. A way to ensure its loss for a price taker player in a competitive market is to limit its decisions with its marginal cost. Given that a company has a profit function of

$$P(q,b) = Pq - a_1 - a_2 q - a_3 (q)^2 \tag{11}$$

the first order derivative of the function with respect to quantity leads to its price and quantity relationship as

$$\frac{dP(q,b)}{dq} = P - a_2 - 2a_3 q = 0 \tag{12}$$

which would lead to the general equation:

$$P = a_2 + 2a_3 q \tag{13}$$

According to the relationship, for the market price P power quantity q is generated. The market price is a stochastic variable that depends on parameters such as the temperature, load, and hour of the day. As mentioned, a forecasted market price for each hour of the next day is provided by the ISO. Notice that this market price is not certain and deviations are expected for each hour. One common approach is to define a search space for the P, and for each market price scenario the corresponding power quantity can be estimated based on the equation given in (13). On the other hand, the standard deviation of each hour that is required for the search space can be estimated based on the historical data. If the forecasted market price is taken as the mean and standard deviation is used, a normal distribution with $N(P,\sigma_t)$ can be used to estimate bid prices. Then the power quantity for block bidding alternative can be calculated as below:

$$q_b = \frac{N(P,\sigma_t) - a_2}{2a_3}\quad \text{where}\quad b_b = N(P,\sigma_t)\quad \text{and}\quad P = \frac{\sum_{t=1}^{24} P_t}{24} \tag{14}$$

Note that the P_t is the forecasted market price that is announced by the ISO. However, deviations would occur in the close range of this price. Hence a normal distribution with mean P_t and standard deviation is used to handle the noise. If K bid quantities (MW h) and bid prices ($/MW h) and M price samples for 24 h are generated, a bid strategy that will return the maximum expected profit over M samples can be found for the block bidding. The pseudo code of the methodology is given in Fig. 3.

Each bidding strategy n, a block of price and corresponding quantity, is evaluated for each price scenario k. Then the average profit is found using N profits. The strategy that returns the highest average profit is selected as the best strategy.

For the hourly bidding, analysis is performed for each hour. For each hour of the day, K bid quantities (MW h) and bid prices ($/MW h) are generated. Then M price scenarios for 24 h are generated. A bidding strategy that will provide the maximum

```
Generate N block of bid quantities and prices
Generate K price samples each for 24 hours
For each n
    For each k
        For each hour t
            If block bid price <= Market price at
                Calculate hourly profit for t
            Else
                Hourly profit for t=0
        Next hour
        Daily profit = Sum (Hourly profit)
```

Fig. 3. Pseudo code of the simulation for block bidding.

```
Generate N hourly bid quantities and prices each consists of 24 pairs
Generate K price samples each for 24 hours
For each n
    For each k
        For each hour t
            If hourly bid price at time t <= Market price at time t
                Calculate hourly profit for t
            Else
                Hourly profit for t=0
        Next hour
        Daily profit = Sum (Hourly profit)
    Next k
Average profit = Sum (Daily profit )/N
Next candidate block
```

Fig. 4. Pseudo code of the simulation for hourly bidding.

expected profit over M samples is found at the end of $N \times M$ simulations. The bid prices and quantities are generated as in (15).

$$q_t = \frac{N(P_t,\sigma_t) - a_2}{2a_3} \quad \text{where} \quad b_t = N(P_t,\sigma_t) \tag{15}$$

Each bidding strategy is a vector of 24 price-quantity pairs and it is evaluated for each price scenario k which is a vector of 24 prices. The average profit is found for each scenario and the strategy that returns the highest average profit is selected. The pseudo code of the algorithm is given in Fig. 4.

5. A case study for Turkish power market

The market price in the Turkish day-ahead market is highly variable and depends on stochastic variables such as generating unit availabilities, total demand, capacities, operational constraints, and fuel costs, among others. The market price fluctuates every hour because of changes of any or all of these stochastic inputs that effect the consumption of electricity. A historical price data set is needed for the analysis. March 7th, 2011, has been chosen arbitrarily, and day-ahead market prices are used to produce 24-h price scenarios. The prices are assumed to deviate from the historical data set and the deviation level is uncertain. To handle the uncertainty, $K=10{,}000$ samples are drawn from a normal distribution with a mean equal to the price at that hour of March 7th and a standard deviation equal to the historical price deviation of that hour. Fig. 5 shows the market price samples and Fig. 6 shows the standard deviation of the market prices for each hour. Note that the day is a typical workday in which the demand is low at night.

Two coal-fired power generators are the source of electricity. Seyitomer is a coal fired power plant located in the midwest of Turkey with a capacity of 600 MW. The Soma coal plant is located in the west of Turkey and has a capacity of 1000 MW. Table 2 provides the details of the units [34]. It is assumed that each generator should bid hourly or determine a block bidding strategy for the market. The unit does not know which strategy to use and if it chooses a strategy in which the bidding price and quantity are unknown. The main objective is to decide the bidding method and bidding prices and quantities that will maximize the expected profit.

The problem involves a huge amount of data interaction and computatinal work. The solution methodology is implemented in visual basic. The simulation is run first and $K=10{,}000$ market price samples are obtained. The next step is to generate $M=10{,}000$ pairs of block bidding strategies, each with a price and power quantity, and $M=10{,}000$ hourly bidding strategies, each of which includes 24 pairs of price and power quantities. This process is repeated for the two units. Each vector of scenarios is then evaluated using price samples as explained in Figs. 3 and 4. The profit for each scenario is found and the statistics for the results of the block and hourly bidding for Seyitomer and Soma are provided in Table 3. The mean profit for block bidding for Seyitomer is 685,020 TL whereas the mean profit for hourly bidding is 621,732 TL. The maximum profit for block bidding is 1227,795 TL whereas the maximum profit for hourly bidding is 1100,198 TL. Standard deviation of profit samples in block bidding is 158,774 and it is 163,882 in hourly bidding. The corresponding results for Soma are also provided in the table. Notice that the mean and maximum profits are higher for block bidding in comparison with the hourly bidding for both units. On the other hand, the standard deviation of the profits of block

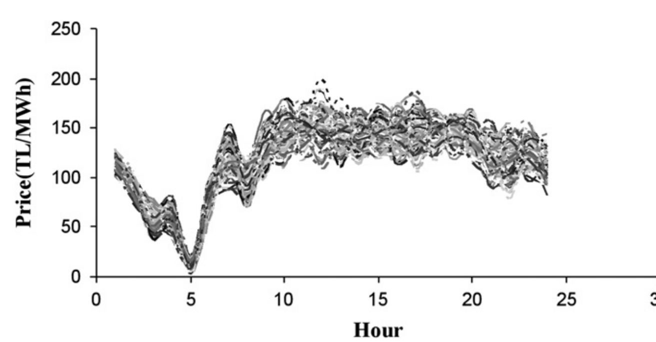

Fig. 5. Hourly day-ahead market price samples.

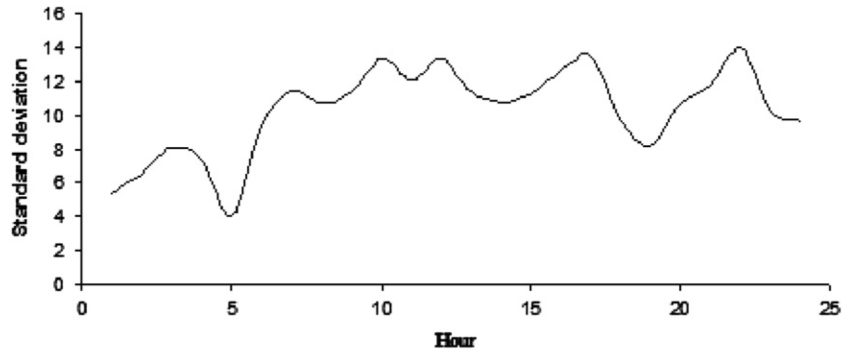

Fig. 6. Standard deviation of hourly price samples.

Table 2
Generator unit characteristics.

	Seyitomer	Soma
a_1	3128	10268
a_2	6.2576	12.4464
a_3	0.0278	0.0336
Capacity (MW)	600	1000

Table 3
Results of the two bidding methods.

	Seyitomer		Soma	
	Block bidding	Hourly bidding	Block bidding	Hourly bidding
Mean profit (TL)	685,020	621,732	793,208	697,650
Maximum profit (TL)	1227,795	1100,198	1607,906	1366,806
Standard deviation	158,774	163,822	209,079	220,991

Table 4
Bid price and quantity for best solution of hourly bidding.

	b_t	q_t
Seyitomer	101	600
Soma	83	1000

bidding is lower than that of hourly bidding in both methods. It shows the solution methodology is robust for different data sets.

Notice that statistical results are calculated based on the 10,000 different bidding scenarios for block and hourly bidding methods and those are evaluated on 10,000 different price samples. It was determined that in the block bidding of Seyitomer, the bid price of b_b(TL/MW h)=101 and the bid quantity of q_b(MW h)=600, and in that of Soma the bid price of b_b(TL/MW h)=83 and the bid quantity of q_b(MW h)=1000. Tables 4 and 5 provide the best solutions for block and hourly bidding strategies, respectively. Note that the model is developed assuming that uniform pricing is used. If the pay-as-bid strategy is preferred, then the problem formulation and the solution will be different.

In uniform pricing, the market mechanism applies pressure on market prices as the units with lower prices have higher chances for dispatching and they will be paid the MCP. Hence, they are more likely to offer lower prices. On the other hand, in pay-as-bid, the participants will be paid what they bid. Therefore, they bid higher prices to maximize their revenue [4,5,17].

Table 5
Bid price and quantity for best solution of hourly bidding.

Hour	Seyitomer		Soma		Hour	Seyitomer		Soma	
	b_t	q_t	b_t	q_t		b_t	q_t	b_t	q_t
1	110.36	600	113.58	1000	13	131.96	600	144.98	1000
2	81.08	600	87.32	1000	14	162.52	600	122.33	1000
3	52.39	600	55.65	642.94	15	149.93	600	148.22	1000
4	52.43	600	72.2	889.25	16	135.97	600	134.29	1000
5	7.5	9.44	13.11	9.92	17	117.78	600	137.84	1000
6	81.83	600	63.72	762.96	18	139.35	600	127.96	1000
7	119.35	600	87.68	1000	19	135.66	600	148.28	1000
8	91.69	600	90.63	1000	20	123.07	600	130.2	1000
9	117.88	600	127.55	1000	21	129.4	600	108.74	1000
10	154.91	600	167.64	1000	22	105.44	600	110.14	1000
11	161.42	600	140.4	1000	23	108.74	600	105.16	1000
12	161.97	600	139.33	1000	24	112.54	600	135.06	1000

The market price plays an important role in the acceptance of bidding offer and profit. If the price is too low, the power producer will not be able to cover its cost and hence either will not be dispatched or will lose money. Fig. 7a and Fig. 8a show the hourly profit distribution for hourly bidding for the Seyitomer and Soma plants and Fig. 7b and Fig. 8b show that of block bidding.

The figures show that the overview of profit distributions follows a similar pattern. However, block bidding returns better profits for all price samples. It is observed that the profits are higher in Fig. 7b and Fig. 8b than in Fig. 7a and Fig. 8a.

The proposed methodology aims to both find the best bidding method and bidding strategy for a price taker unit. Hence, it is different from the research given in [10] and [15]. In [15], the marginal cost based bidding is not considered and no bidding scenarios are included. In [10], the marginal cost is included and a probabilistic method is proposed and a piecewise bidding structure is used. In this paper, both price samples and bid samples are considered and no limits on the bidding structure are imposed. The best strategy is searched for on the edge of market prices and the corresponding power quantity which is derived from the marginal cost. A two-sided search is performed in both market prices and bid samples. Hence, as the number of simulations is large enough, it is more likely that a wider search space is scanned and a better solution is reached in comparison with the other proposed methods.

6. Conclusions

Bidding into the market is an important process in competitive markets that need to be carefully handled. The right bidding methodology should be selected and then the right price and corresponding power quantity need to be determined within a

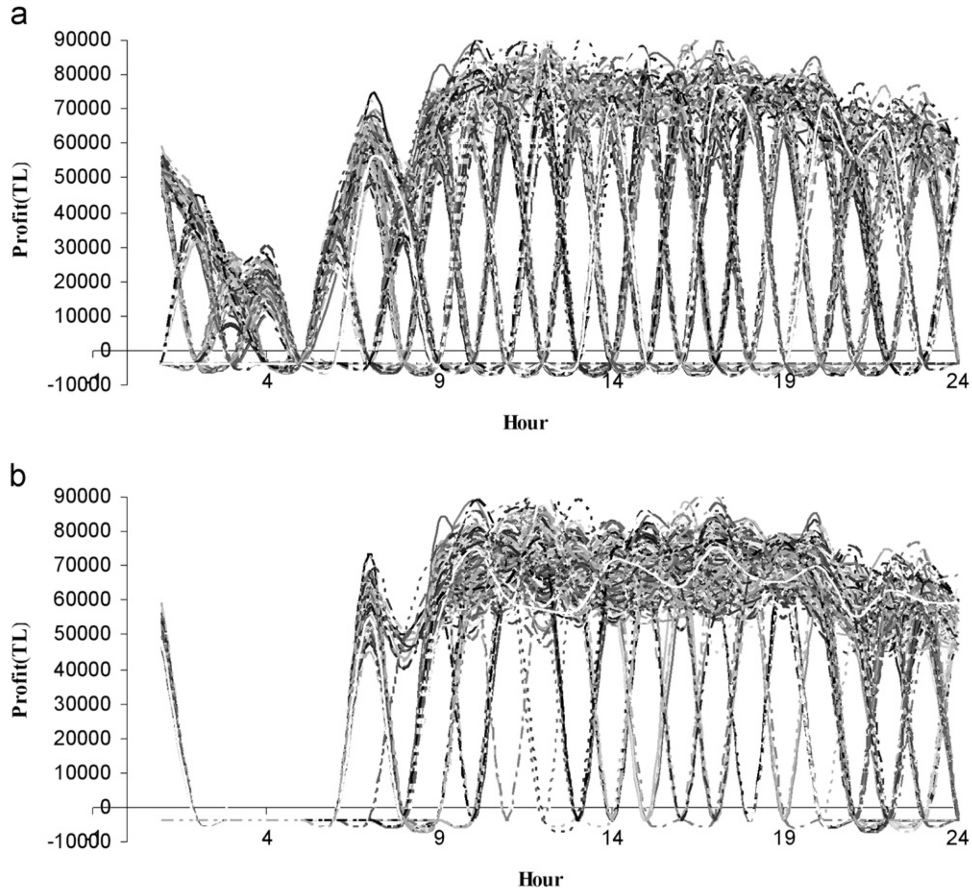

Fig. 7. (a) Profits in hourly bidding in Seyitomer (b) profits in block bidding in Seyitomer.

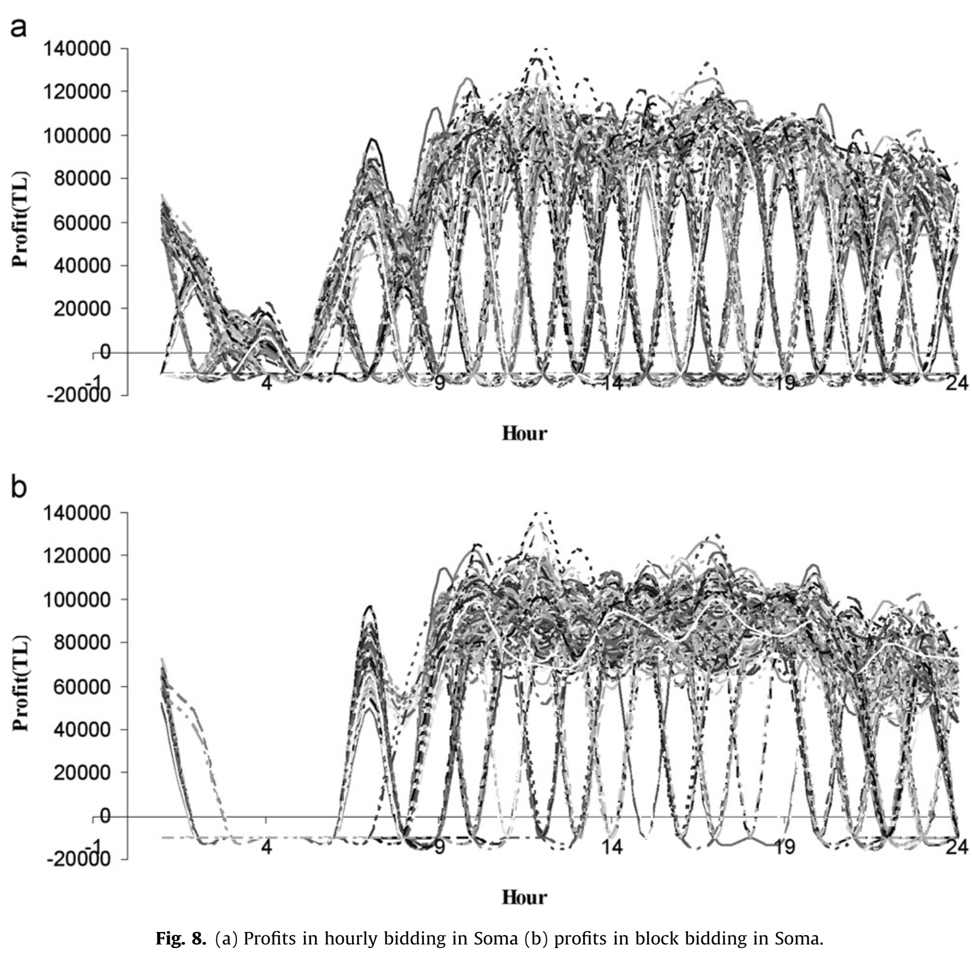

Fig. 8. (a) Profits in hourly bidding in Soma (b) profits in block bidding in Soma.

limited time frame and under uncertain market conditions with imperfect information. In this paper, the deregulation, power supply and bidding in Turkish market are examined. A generator needs to select an hourly bidding or block bidding methodology when they submit an offer to the market. Two models for each bidding methodology are proposed for a price taker unit that aims to maximizes its profit under uncertain market prices. To handle the uncertainty in market prices, historical price data and standard deviation of the prices are used to get normally generated price samples. Finally, a marginal cost and market price based bid scenario estimation method is developed to solve the problem.

The solution approach includes a market price generation module and a bid strategy generation method that incorporates the marginal cost of the generating unit. Two generators, Seyitomer and Soma, were selected for the case study. The solution methodology is run and the bidding methodology and the bid prices and quantities are determined for each plant. The results show that block bidding returns higher profits with lower standard deviation over 10,000 price samples. In block bidding, a bid price that is sufficient to cover the power generation cost is submitted to the market. In hourly bidding, on the other hand, the profit for each hour is lower than the block bidding, as for some hours not bidding achieves better results. Hourly profit distributions also show that it is not likely to make a profit for all hours and the company should focus on those hours when the power price is higher. The results also show that the methodology is robust and it can be used to determine the bidding method and strategies used by power units.

References

[1] Ilic M, Galiana F, Fink L. Power systems restructuring: engineering and economics. Boston, US: Kluwer; 1998.
[2] Wen F, David AK. Optimal bidding strategies and modeling of imperfect information among competitive generators. IEEE Transactions on Power Systems 2001;16(1):15–21.
[3] Liu Y, Wu FF. Generator bidding in oligopolistic electricity markets using optimal control: fundamentals and application. IEEE Transactions on Power Systems 2006;21(3):1050–61.
[4] David, AK, Wen,F. 2000, Strategic bidding in competitive electricity markets: a literature survey. In: IEEE power engineering summer meeting. July, 16–20: Seattle, WA; (4) p. 2168–2173.
[5] Kian A, Cruz JB. Bidding strategies in dynamic electricity markets. Decision Support Systems 2005;40(3–4):543–51.
[6] Song Y, Ni Y, Wen F, Hou Z, Wu F. Conjectural variation based bidding strategy in spot markets: fundamentals and comparison with classical game theoretical bidding strategies. Electric Power Systems Research 2003;67(1):45–51.
[7] Richter CW, Sheble GB. Genetic algorithm evolution of utility bidding strategies for the competitive marketplace. IEEE Transactions on Power Systems 1998;13(1):256–61.
[8] Rodriguez CP, Anders GJ. Bidding strategy design for different types of electric power market participants. IEEE Transactions on Power Systems 2004;19(2): 964–71.
[9] Zhang D, Wang Y, Luh PB. Optimization based bidding strategies in the deregulated market. IEEE Transactions on Power Systems 2000;15(3):981–6.
[10] Conejo AJ, Nogales FJ, Arroyo JM. Price-taker bidding strategy under price uncertainity. IEEE Transactions on Power Systems 2002;17(4):1081–8.
[11] Ladurantaye D, Gendreau M, Potvin J. Strategic bidding for price-taker hydroelectricity producers. IEEE Transactions on Power Systems 2007;22(4): 2187–203.
[12] Fleten SE, Pettersen E. Constructing biding curves for a price-taking retailer in the Norwegian electricity market. IEEE Transactions on Power Systems 2005;20(2):701–8.
[13] Dicorator M, Forte G, Trovato M, Caruso E. Risk-constrained profit maximization in day-ahead electricity market. IEEE Transactions on Power Systems 2009;24(3):1107–14.
[14] Zhang G, Zhang G, Gao Y, Lu J. Competitive strategic bidding optimization in electricity markets using bilevel programming and swarm technique. IEEE Transactions on Industrial Electronics 2011;58(6):2138–46.
[15] Shrestha, GB , Qiao, S. Bidding strategy for price-taker distributed Genco in competitive electricity market. In: International power engineering conference. IPEC: 27–29 Oct.; 2010. p. 863–868.
[16] Bezerra B, Barroso LA, Pereira MV. Bidding strategies with fuel supply uncertainty in auctions of long-term energy call options. IEEE Transactions on Power Systems 2011;26(2):653–60.
[17] Kwon RH, Frances D. Optimization-based bidding in day-ahead electricity auction markets: a review of models for power producers, in; handbook of networks in power systems I. Energy Systems 2012:41–59.
[18] Li T, Shahidehpour M. Strategic bidding of transmission constrained GENCOs with incomplete information. IEEE Transactions on Power Systems 2005;20(1): 437–47.
[19] Kanakasabapathy K, Swarup S. Bidding strategy for pumped-storage plant in pool-based electricity market. Energy Conversion and Management 2010;51(3):572–9.
[20] Badri A, Jadid S, Rashidinejad M, Moghaddam MP. Optimal bidding strategies in oligopoly markets considering bilateral contracts and transmission constraints. Electric Power Systems Research 2008;78(6):1089–98.
[21] Aggarwal SK, Saini LM, Kumar A. Electricity price forecasting in deregulated markets: a review and evaluation. International Journal of Electrical Power & Energy Systems 2009;31(1):13–22.
[22] Amjady N, Daraeepour A, Keynia F. Day-ahead electricity price forecasting by modified relief algorithm and hybrid neural network. IET Generation, Transmission & Distribution 2010;4(3):432–44.
[23] Singhal D, Swarup KS. Electricity price forecasting using artificial neural networks. International Journal of Electrical Power & Energy Systems 2011;33(3):550–5.
[24] Pindoriya NM, Singh SN, Singh SK. An Adaptive wavelet neural network-based energy price forecasting in electricity markets. IEEE Transactions on Power Systems 2008;23(3):1423–32.
[25] EPDK, Enerji piyasasi duzenleme ve denetleme kurumu [online] www.epdk.gov.tr (accessed: April, 2011).
[26] Baldick R. Electricity market equilibrium models: the effect of parameterization. IEEE Transactions on Power Systems 2002;17(4):1170–6.
[27] Wood AJ, Wollenberg BF. Power generation, operation and control. 2nd ed. New York: John Wiley & Sons, Inc.; 1996 31-32.
[28] Cain, BM, Alvarado, LA. Implications of cost and bid format on electricity market studies: linear versus quadratic costs. In: Large engineering systems conference on power engineering. Halifax: Canada; July, 2004.
[29] Baldick,R. Computing the electricity market equilibrium: uses of market equilibrium models. In: Power systems conference and exposition; 2006. p. 66–73.
[30] Yucekaya A, Valenzuela J, Dozier G. Strategic bidding in electricity markets using particle swarm optimization. Electric Power Systems Research 2009;79(2): 335–45.
[31] Gore O, Viljainen S, Makkonen M, Kuleshov D. Russian electricity market reform: deregulation or re-regulation. Energy Policy 2012;41:676–85Pp 2012;41:676–85.
[32] Nasrollahi Shahri, Nima. (2011), Power market reforms and privatization of the electricity industry in the Iranian energy sector; an uphill struggle? In: MPRA paper no. 28047, 22:05 Online at 〈http://mpra.ub.uni-muenchen.de/28047/〉.
[33] Al-Sunaidy A, Green R. Electricity deregulation in OECD (organization for economic cooperation and development) countries. Energy 2006;31:769–87 Issues 6–7.
[34] Kurban, M, Başaran, Ü. Türkiye'deki 380 kV'luk 14 Baralı Güç Sisteminde Ekonomik Yüklenme Analizi, Elektrik-Elektronik-Bilgisayar Mühendisliği, 11. National Congress, 22–25 September; 2005. İstanbul, Turkey.